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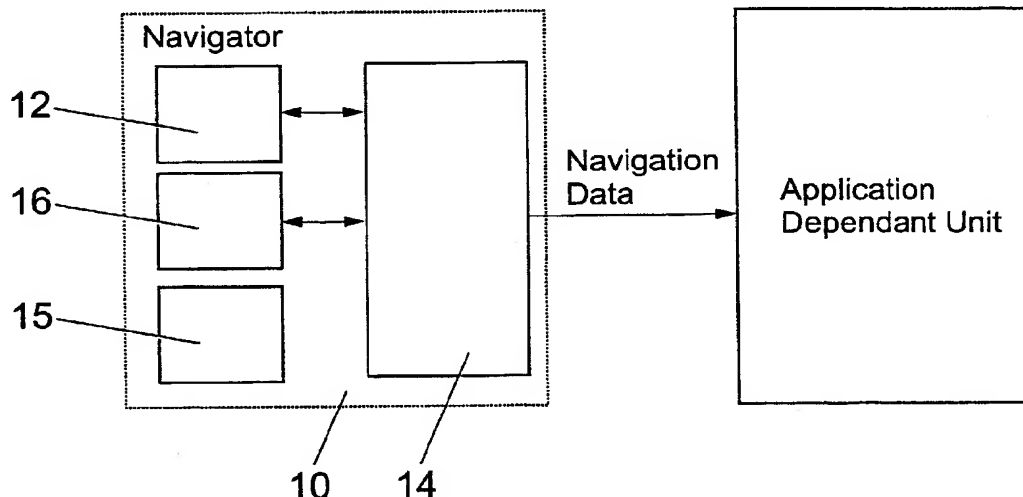
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(54) Title: NAVIGATION APPARATUS AND METHOD



(57) Abstract: A navigation apparatus and method is described as comprising an inertial navigation sensor having a data output, and a processor adapted to be coupled to the data output. The processor is capable of performing a non-linear processing of the data output. Preferably, the apparatus and method are characterised in that a GPS (or similar satellite system) is provided where data output from the GPS is provided to the processor. Preferably, the apparatus and method are further characterised in that the processor comprises an artificial neural network, and the inertial navigation sensor is moved between at least two known locations during the training of the artificial neural network.

1 "Navigation Apparatus and Method"

2

3 The present invention relates to a navigation apparatus
4 and method, and more particularly, but not exclusively,
5 relates to a navigation apparatus and method for a wide
6 range of applications such as vehicles, such as motor
7 cars, motor bikes, boats, ships, vans, lorries, trains,
8 aircraft, hovercraft, balloons, gliders and the like,
9 or any application which requires a navigational
10 reference platform, as well as other applications such
11 as drilling boreholes in the ground for purposes such
12 as the exploration of hydrocarbons and other
13 applications where knowledge of the navigation of a
14 person or object is required, such as munitions,
15 ordinance, missiles, rocketry and any other military or
16 civilian application, as well as subsea and underwater
17 vehicles, humans under ground, animals such as wildlife
18 tagging etc.

19

20 The majority of commercial aircraft utilise an Inertial
21 Navigation System (INS) to permit the pilot to navigate
22 the aircraft entirely independently of any external
23 reference signals such as the Global Positioning System
24 (GPS) operated by the United States Department Of
25 Defence (USDOD) or the many different aviation

1 navigation beacons that are available. INS was
2 originally developed for intercontinental ballistic
3 missiles and comprises a series of two or three
4 orthogonally mounted gyroscopes and three
5 accelerometers to measure minute changes in the
6 vehicle's acceleration; in other words, the gyroscopes
7 and accelerometers measure very small angular rotations
8 and g-forces. By mathematically or electronically
9 integrating these g-forces, the INS is able to
10 determine positional changes in the vehicles position,
11 and given a known starting location, the INS the
12 current position can be determined.

13
14 However, the mathematical process of integration of the
15 vehicle acceleration unavoidably involves small errors
16 due to the mechanical tolerances involved in the
17 gyroscopes and accelerometers. These small errors,
18 when integrated and multiplied by time to compute the
19 positional variations of the vehicle, cause a long term
20 "drift" in the calculated position of the INS. An
21 aircraft, using a commercial INS unit, crossing the
22 Atlantic from Heathrow airport can be 3km away from its
23 true position when it finally reaches the East coast of
24 the USA.

25
26 Furthermore, commercial aviation INS cost upwards of
27 US\$ 100,000 and are therefore aimed at professional,
28 safety critical applications.

29
30 Satellite navigation systems, such as the US Navstar
31 GPS, the Russian GLObal Navigation System (GLONASS) and
32 the European Geostationary Navigation Overlay Service
33 (EGNOS) are also well known. The GPS in particular has
34 already revolutionised the ground transportation
35 sector, and GPS can commonly be found on-board cars,
36 trucks, boats and small aircraft and are widely used by

1 recreational sailors, climbers and hikers. Key factors
2 of the success of GPS are the low-cost and
3 miniaturisation of the GPS receivers. However, because
4 of their poor short-term navigation performance and the
5 requirement to always have a number of the Navstar
6 satellites in sight, navigation applications based on
7 GPS receivers are in fact limited. Furthermore, GPS
8 suffers from the well known "Urban Canyon" effect which
9 results from the screening of the GPS antenna by the
10 buildings in a typical urban city centre. In fact, the
11 GPS signal level is very low, and almost any
12 obstruction such as a tree branch will attenuate the
13 signal sufficiently to prevent reception of the signal
14 from the satellite by the GPS receiver. Furthermore,
15 the USDOD has previously applied Selective Availability
16 (SA) to the GPS signal, where SA is a deliberate
17 degradation intended to deny access to the full GPS
18 accuracy to non-US approved personnel. SA imposes a
19 100m 95% Circle Error Probability (CEP), which means
20 that 95% of the reported positions from a GPS receiver
21 should be within 100m of the true location. This does
22 not take into account signal degradation due to
23 propagation or geometrical precision dilution effects.

24
25 INS provides accurate information on position, speed
26 and attitude, at a relatively high rate, but is only
27 generally effective over short periods due to the
28 accumulation of the INS sensor errors. A GPS receiver
29 with a single antenna can provide position and speed,
30 but if there are only three satellites in the line of
31 sight of the antenna then the GPS generally cannot
32 provide attitude although it can do so if there are
33 four satellites in the line of sight of the antenna.
34 The GPS provides this data at a relatively low rate,
35 but with excellent long term position accuracies.

36

1 It is therefore desirable, for applications where it is
2 possible to use GPS, to integrate the output of the INS
3 and GPS to combine the advantages of both systems
4 whilst avoiding many of the disadvantages of each
5 system in isolation. A conventional way of doing this,
6 particularly for military applications is to use a
7 Kalman Filter which takes two independent measurements
8 of the same quantity, where each of the two
9 measurements has its own independent error sources, and
10 integrates them together to provide an improved
11 estimate of the quantity with an associated error less
12 than or equal to either of the original errors. A
13 detailed understanding of the mathematics behind Kalman
14 Filters reveals that the two criteria that are
15 important for the operation of a Kalman Filter are the
16 independence of the error sources and the linearity of
17 the sensors. Therefore, if the error sources are not
18 independent, or the sensors are non-linear, then the
19 estimate will be worse than either of the original
20 estimates, not better. Conventional INS devices are
21 linear and are thus suitable for use with a Kalman
22 Filter.

23
24 According to a first aspect of the present invention,
25 there is provided a navigation apparatus comprising
26 an inertial navigation sensor having a data output, and
27 a processor adapted to be coupled to the data output,
28 the processor being capable of performing a non-linear
29 processing of the data output.

30
31 According to a second aspect of the present invention,
32 there is provided a method of providing navigation
33 information, the method comprising providing an
34 inertial navigation system having a non-linear output,
35 and processing the non-linear output with a processor.
36

1 Preferably, the first and second aspects of the
2 invention are characterised in that a GPS (or similar
3 satellite system) is provided where data output from
4 the GPS is provided to the processor.

5
6 Preferably, the first and second aspects of the
7 invention are further characterised in that the
8 processor comprises an artificial neural network, and
9 the inertial navigation sensor is moved between at
10 least two known locations during the training of the
11 artificial neural network.

12
13 Typically, a portion or all of the processing may be
14 conducted in a simulated manner. Alternatively, the
15 processing may be conducted by a processor mounted on
16 the apparatus.

17
18 Preferably, a GPS (or similar satellite system) may
19 also be provided where data output from the GPS is
20 provided to the processor.

21
22 Typically, the processor is a pattern classifier
23 processor, and preferably includes an artificial neural
24 network.

25
26 Preferably, the navigation apparatus is provided within
27 a housing which may be mounted on an object, person,
28 animal, tool, vehicle, or any item for which knowledge
29 of its navigation is desired.

30
31 Preferably, the inertial navigation sensor comprises
32 two, or more preferably three orthogonally arranged
33 sensors. Preferably, the inertial navigation sensors
34 are solid-state devices and more preferably, are solid-
35 state accelerometers which may comprise a silicon
36 etching formed in silicon wafer.

1 The advantage of using such a solid state accelerometer
2 is that it is relatively inexpensive.

3
4 The artificial neural network may optionally be in the
5 form of a Kohonen Feature map or Self-Organising Map
6 (SOM).

7
8 The artificial neural network is typically trained
9 initially, and typically has a training phase performed
10 upon it.

11
12 Typically, the patterns used to train the artificial
13 neural network represent pattern that will be observed
14 in the real data used during the "execution" phase of
15 operation. Preferably, many training cycles are
16 conducted during the training phase.

17
18 Preferably, the artificial neural network is trained in
19 an unsupervised manner. Typically, data representing
20 the known location is input to the artificial neural
21 network during the labelling phase of the unsupervised
22 training.

23
24 Alternatively, the artificial neuron network is trained
25 in a supervised manner.

26
27 With regard to supervised training, preferably by use
28 of a Backpropagation algorithm, the artificial neuron
29 network adjusts its internal weights. Preferably, data
30 representing the known locations is input to the
31 artificial neural network, prior to the next set of
32 data for the next location being input from the
33 inertial navigation sensor, such that the artificial
34 neural network learns the difference between the output
35 of the inertial navigation sensor versus the data
36 representing the known location.

1 Typically, the inertial navigation sensor is moved
2 between many known locations of a track, such as a
3 track arranged within a laboratory, where the spacial
4 location of many points on the track have been
5 previously and accurately surveyed.

6
7 Embodiments of the present invention will now be
8 described, with reference to the accompanying drawings,
9 in which:-

10 Fig. 1 is a block diagram of a navigation system
11 in accordance with the present invention; and
12 Fig. 2 is a schematic representation of a portion
13 of a Neural Network for illustrative purposes.

14
15 Fig. 1 shows a schematic block diagram of the main
16 components of a navigation system 10 in accordance with
17 the present invention. The navigation system
18 optionally comprises a commercially available GPS or
19 DGPS receiver 12, where data output of this optional
20 GPS/DGPS receiver 12 is connected by any suitable means
21 such as electrical wiring to a processing module 14.
22 An electrical power supply 15, which may be any
23 suitable power supply, is also provided.

24
25 An INS 16 is also provided, and has its data output
26 connected by any suitable means to the processing
27 module 14. The INS 16 preferably comprises three
28 orthogonally arranged miniature solid-state
29 accelerometers, examples of which are manufactured by
30 ANALOGUE DEVICES, in that the three accelerometers are
31 mounted perpendicularly to one another. Additionally,
32 the INS 16 comprises two orthogonally mounted
33 gyroscopes which can be used to measure the rotation of
34 the INS.

35
36 The solid state accelerometer 16 comprises a sub-

1 miniature silicon "beam" etched into the silicon wafer.
2 The beam deflects or bends under the applied g-forces
3 experienced by the INS 16, and the deflection of the
4 beam can be measured by a number of methods
5 electronically.

6
7 The advantage of using such a solid state accelerometer
8 is that it is relatively inexpensive. Hitherto, such
9 solid state accelerometers have only been known for use
10 in the anti-shake "Steady Shot" mechanisms utilised in
11 consumer handheld camcorders, and such solid state
12 accelerometers are extensively non-linear in that there
13 is not a linear relationship between the acceleration
14 and the output voltage. In other words, if the
15 acceleration is doubled, the output voltage does not
16 double, but rather varies in a complex manner with
17 acceleration. Furthermore, such solid state
18 accelerometers suffer from a pronounced resonant
19 frequency as a result of the dimensions of the silicon
20 beam employed in the accelerometer, which produces a
21 marked non-linearity in the sensitivity of the device
22 under vibrational conditions. As a result, such solid
23 state accelerometers have hitherto been considered to
24 be entirely unsuitable for use within an INS
25 environment.

26
27 The processing module 14 comprises a non-linear
28 processor, which is in essence a pattern classifier, in
29 the form of an Artificial Neural Network (ANN).
30 Depending upon which training method is to be utilised
31 (details of which follow) the ANN may be in the
32 specialised form of a Kohonen Feature map or Self-
33 Organising Map (SOM).

34
35 The ANN comprises a networked array of neurons, and in
36 its hardware implementation, the number of neurons is

1 only limited by the number that can be provided on a
2 silicon chip. At present, it is proposed to use a
3 silicon chip with 256 neurons thereon, but this figure
4 will increase substantially over time as the technology
5 improves.

6
7 The ANN effectively has two phases of operation, these
8 being "training" and "execution" and which will be
9 detailed subsequently. The ANN requires to be trained
10 on example data, and this will also be detailed
11 subsequently.

12
13 The ANN 14 is a probabilistic device with each neuron
14 in the network being initialised with a series of
15 random "weights", where the weights determine the
16 relationship between the different inputs fed to a
17 neuron. As a result, the convergence on the patterns
18 in the input data is purely one of statistical chance.
19 For example, with a particular distribution of initial
20 weights, on one occasion the ANN 14 may converge on a
21 particular pattern in the input data set, and on
22 another occasion with a different weight distribution,
23 this pattern may be missed.

24
25 The patterns used to train the ANN 14 should be typical
26 of the patterns that will be observed in the real data
27 used during the "execution" phase of operation. It
28 should be noted that the quality or relevance of the
29 training data will have a major impact on the
30 capability of the ANN 14 during execution. If the ANN
31 14 has not been trained on data containing examples of
32 patterns that are of interest, then it will be unable
33 to identify such patterns in the execution phase.
34 Additionally, like biological neural systems, the ANN
35 14 must be shown many examples of the training data,
36 and it may be necessary to have a training run

1 containing hundreds of thousands of cycles.

2

3 Initially, the ANN 14 requires to be trained on example
4 data, and there are typically two different methods of
5 training the ANN 14, supervised and unsupervised.

6

7 With regard to supervised training, the input data are
8 fed from the GPS/DGPS 12 (if present) and/or the INS 16
9 into the ANN 14, while the known location of the
10 navigation system 10 (which is known from previously
11 conducting an accurate survey of the location) is also
12 fed to the ANN 14. The ANN 14 then attempts, by use of
13 a Backpropagation algorithm as described by J.J.
14 Hopfield, "Neural networks and physical systems with
15 emergent collective computational abilities" in the
16 Proceedings of the National Academy of Sciences
17 79:2554-2558, 1982, to adjust its internal weights so
18 as to best represent the input data. The navigational
19 system 10 may be moved through a number of known
20 locations and hence the ANN 14 will be receiving data
21 from the GPS/DGPS 12 (if present) and/or the INS 16,
22 each of which represent an independent estimate of the
23 position of the system 10. However, it should be borne
24 in mind that each of the two data sets contain errors,
25 in that the data are "noisy". At each training step,
26 the actual location is fed to the ANN 14 and the ANN 14
27 attempts to adjust its internal weights so that its
28 output is close to the actual location value.

29

30 After sufficient training of the ANN 14 has occurred,
31 in that the ANN 14 understands the relationship between
32 the GPS/DGPS (if present) and/or INS data, the training
33 phase is concluded and the execution phase is
34 commenced.

35

36 The execution phase consists of moving the navigation

1 system 10 to an unknown location and the ANN 14, since
2 it understands the relationship between the GPS/DGPS 12
3 (if present) and/or the INS 16, will provide an output
4 that represents the corrected position of the
5 navigational system 10. It should be noted that this
6 positional estimate will be subject to error in the
7 same way as before.

8
9 In order to clarify the nature of the supervised method
10 of training, an example is now given of a training
11 exercise for another application, specifically Optical
12 Character Recognition (OCR). In this OCR application,
13 data are provided by either a digital camera, or a
14 scanner positioned over the character to be recognised.
15 Fig. 2 shows a typical arrangement for an ANN 20 used
16 in an OCR application, where the data provided by the
17 camera or scanner are input into the ANN 20 at
18 locations 18a to 18z. The data input will usually be
19 in the form of pixel data from the camera. The ANN 20
20 has a number of outputs A to Z, each representing a
21 letter from the alphabet. The ANN 20 further comprises
22 an array of neurons 22 which are networked. In
23 general, the desired result in this OCR application is
24 that when the camera/scanner views the letter A, the A
25 output of the ANN 20 should be activated whilst the
26 other B to Z outputs are not active. The ANN 20 is
27 "trained" by inputting the pixel data for the letter A
28 into the inputs 18a to 18z. The weights in the neurons
29 22 are initially random, with the result that the
30 outputs A to Z indicate a random pattern. The desired
31 output of A is now shown to the ANN 20, and by using
32 its training algorithm, such as the Backpropagation
33 algorithm as described in the aforementioned J.J.
34 Hopfield publication, the ANN 20 tries to adjust its
35 weights so as to make the A output a 1 (that is,
36 active) and the B to Z outputs a 0 (that is, inactive).

1 The training is continued by showing the ANN 20
2 thousands of examples of the letter A as well as the
3 letters B to Z. For each time that the ANN 20 is input
4 with data relating to a letter, the ANN is shown what
5 the correct result should be. As training is
6 progressed, the ANN should start to converge on the
7 correct result, and hence no longer outputs a random
8 result, such as when the ANN is shown the letter A, the
9 A output is close to a 1 whilst the B to Z outputs are
10 close to 0. The more training that is given to the ANN
11 20, then the accuracy of the ANN 20 will increase,
12 until the accuracy is acceptable, at which stage, the
13 training phase can be stopped, and the execution phase
14 can be commenced.

15
16 In the execution phase, the ANN 20 is now shown an
17 unknown letter (i.e. form a text that is to be the
18 subject of the OCR) by having the pixel data fed into
19 the inputs 18a to 18z. The correct output should be
20 close to a 1 whilst the other outputs should all be
21 close to a zero.

22
23 With regard to the unsupervised training method, this
24 requires the ANN 14 to be in the specialised form of
25 the SOM. This unsupervised training method does not
26 require training data to be used, but rather the SOM
27 attempts to form internal classifications of
28 significant clusters of data observed in the input
29 data. The SOM 14 is trained by moving the navigational
30 system 10 through a wide variety of unknown positions,
31 without showing the SOM 14 at each location what the
32 correct value is for the location. The SOM 14 then
33 classifies the relationships between the input data in
34 a suitable manner, such as described in Tuero Kohonen
35 "Analysis of a Simple Self-Organising Process"
36 Biological Cybernetics 44(2):135-140, 1982 publication.

1 Once sufficient training cycles have been completed,
2 the SOM 14 is then subjected to a "labelling" phase,
3 which consists of moving the SOM 14 through a number of
4 known test locations which have been previously
5 accurately surveyed. This knowledge of the spacial
6 location of the test locations is used to label the
7 activated SOM 14 neurons in an appropriate manner, such
8 as described in Tuero Kohonen "Self-Organising Maps"
9 Springer Series in Information Sciences, 1995. After
10 this labelling phase has been concluded, the weights of
11 the neurons in the SOM 14 are "frozen", and the SOM 14
12 can enter the execution phase.

13
14 Use of the navigation system 10 is now permitted, since
15 the GPS/DGPS 12 (if present) and/or the INS 16 provide
16 data to the SOM 14 which has been trained to recognise
17 the relationship between the SA GPS/DGPS 12 (if
18 present) and the non-linear and resonant INS 16.
19 Hence, the SOM 14 output provides an improved estimate
20 of the position of the navigational system 10 since the
21 SA error experienced by the GPS 12 is entirely
22 independent of the non-linearity and resonance
23 experienced by the INS 16.

24
25 In order to clarify the nature of the unsupervised
26 method of training, an example is now given of a
27 training exercise for another application, specifically
28 facial recognition. An SOM used in that application
29 may be shown thousands of faces without telling the SOM
30 which face belongs to which person. The SOM will
31 hopefully classify faces from the same person into the
32 same category, and those of different people into
33 respective different categories. After this training
34 phase has been concluded, the labelling phase is
35 commenced in which the SOM is shown individual examples
36 (only one is required) of each of the faces. Then

1 observation is done for the clusters of neurons in the
2 SOM which are activated or excited by that face, and
3 those clusters of activated neurons are labelled to
4 represent the name of the person whose face is being
5 used.

6
7 It should be noted that there is a great advantage in
8 using the unsupervised method of training for the
9 ANN/SOM 14, in that the initial training phase can be
10 conducted in a simulation environment by computer,
11 which enables extensive training of the SOM to be
12 undertaken with minimal inconvenience. The simulation
13 environment contains a mathematical model of the INS 14
14 and the GPS 12 (if present), where the mathematical
15 model is created using the manufacturer's
16 specifications. The simulated navigational system 10
17 is taken over a varied and extensive training track
18 within the simulation environment. During this
19 training the outputs of the GPS 12 and INS 16 are
20 computed and fed into the program which is simulating
21 the SOM 14. A suitable program for simulating the SOM
22 14 is MATLAB (RTM) which is offered by THE MATH WORKS,
23 INC. Hence, the simulated SOM 14 "learns" about the
24 relationship between the INS 16 and the GPS 12,
25 including the effects of INS drift and GPS SA.
26 Typically, thousands of training cycles will be
27 required in the simulation.

28
29 The simulation models are, however, inevitably somewhat
30 limited in accuracy. For this reason, a physical
31 navigation system 10 is created, and the physical SOM
32 14 is initialised using the data from the simulation;
33 that is the simulated SOM 14 neuron weights. These
34 simulated data provides a good starting point, since
35 the INS 16 and GPS 12 models are reasonably accurate.
36 Hence, the final training required to optimise the SOM

1 weight vectors is much reduced. The final training of
2 the SOM 14 is concluded in the same manner as detailed
3 above.

4

5 Once the SOM 14 of the test rig has been fully trained,
6 the SOM 14 weight vectors can be transferred to
7 production units manufactured by mass production
8 techniques. These production units do not require
9 significant additional training since the weights from
10 the SOM 14 of the test rig represent the relationship
11 between the GPS 12 and INS 16 modules.

12

13 In practice, there may be some variation between
14 production solid-state sensors due to the natural
15 manufacturing tolerances. Post-production training can
16 be conducted in a similar manner to the test rig
17 training if required.

18

19 Tests have been conducted that reveal that given a
20 known starting point (to take out the effects of GPS
21 SA), the navigational system 10 experiences a 30cm/hour
22 short term drift. Long term drift is limited by the
23 basic GPS accuracy of 1-3 metres. Therefore, during
24 "urban canyons", the INS provides good short term
25 accuracy of 30cm/hour. Over longer term use, there
26 should be a maximum drift of 3 metres assuming that the
27 GPS 12 is present. Furthermore, the SA is removed
28 because of its semi-periodic nature, with the INS 16
29 providing the short term navigational reference.

30

31 It should be noted that the GPS 12 could be omitted
32 from the navigation system 10, and the navigation
33 system 10 could be used for applications where there is
34 no line of sight to a GPS Navstar satellite, such as
35 included in a downhole string which is inserted into a
36 borehole in the earth such as an oil or gas well, since

1 the INS 16 will provide at least a reasonable short
2 term accuracy.

3
4 Furthermore, it is envisaged at present that the
5 ANN/SOM 14 will be implemented in a hardware unit.
6 However, it is also foreseen that a software
7 implementation of the ANN/SOM 14 could be achieved,
8 where the software program is run on Digital Signal
9 Processing (DSP) chips as these become more powerful in
10 order to allow a real time software implementation.

11
12 Modifications and improvements can be incorporated
13 without departing from the scope of the invention. For
14 instance, the navigation system 10 could be
15 incorporated into a vehicle (not shown) to permit an
16 operator of the vehicle to monitor the speed of the
17 vehicle, thus gaining independence from the
18 conventional vehicle electronics which currently
19 monitor the speed.

1 **CLAIMS**

2

3 1. A navigation apparatus comprising an inertial
4 navigation sensor having a data output, and a processor
5 adapted to be coupled to the data output, the processor
6 being capable of performing a non-linear processing of
7 the data output, characterised in that a GPS (or
8 similar satellite system) is provided where data output
9 from the GPS is provided to the processor.

10

11 2. Apparatus according to claim 1, wherein a portion
12 or all of the processing is conducted in a simulated
13 manner.

14

15 3. Apparatus according to claim 1, wherein the
16 processing is conducted by a processor associated with
17 the apparatus.

18

19 4. Apparatus according to any preceding claim,
20 wherein the processor is a pattern classifier
21 processor.

22

23 5. Apparatus according to any preceding claim,
24 wherein the processor comprises an artificial neural
25 network.

26

27 6. Apparatus according to any preceding claim,
28 wherein the navigation apparatus is provided within a
29 housing which is mounted on an object, person, animal,
30 tool, vehicle, or any item for which knowledge of its
31 navigation is desired.

32

33 7. Apparatus according to any preceding claim, where
34 the inertial navigation sensor comprises three
35 orthogonally arranged sensors.

36

1 8. Apparatus according to claim 7, wherein the
2 inertial navigation sensors are solid-state devices.

3

4 9. Apparatus according to claim 7, wherein the
5 inertial navigation sensors are solid-state
6 accelerometers.

7

8 10. Apparatus according to claim 9, wherein the solid-
9 state accelerometers comprise a silicon etching formed
10 in silicon wafer.

11

12 11. Apparatus according to claim 5, wherein the
13 artificial neural network is in the form of a Kohonen
14 Feature map.

15

16 12. Apparatus according to claim 5, wherein the
17 artificial neural network is in the form of a Self-
18 Organising Map (SOM).

19

20 13. Apparatus according to any of claims 5, 11 or 12,
21 wherein the artificial neural network has a training
22 phase performed upon it.

23

24 14. Apparatus according to claim 13, wherein patterns
25 used to train the artificial neural network represent
26 patterns that will be observed in the real data used
27 during the "execution" phase of operation.

28

29 15. Apparatus according to either of claims 13 or 14,
30 wherein the artificial neural network is trained in an
31 unsupervised manner.

32

33 16. Apparatus according to either of claims 13 or 14,
34 wherein the artificial neuron network is trained in a
35 supervised manner.

36

1 17. Apparatus according to claim 16, wherein a
2 Backpropagation algorithm is utilised, whereby the
3 artificial neuron network adjusts its internal weights.
4

5 18. A method of providing navigation information, the
6 method comprising providing an inertial navigation
7 system having a non-linear output, and processing the
8 non-linear output with a processor, characterised in
9 that a GPS (or similar satellite system) is also
10 provided where data output from the GPS is provided to
11 the processor.
12

13 19. A navigation apparatus comprising an inertial
14 navigation sensor having a data output, and a processor
15 adapted to be coupled to the data output, the processor
16 being capable of performing a non-linear processing of
17 the data output, characterised in that the processor
18 comprises an artificial neural network, and the
19 inertial navigation sensor is moved between at least
20 two known locations during the training of the
21 artificial neural network.
22

23 20. Apparatus according to claim 19, wherein a portion
24 or all of the processing may be conducted in a
25 simulated manner.
26

27 21. Apparatus according to claim 19, wherein the
28 processing is conducted by a processor associated with
29 the apparatus.
30

31 22. Apparatus according to any of claims 19 to 21,
32 wherein a GPS (or similar satellite system) is also
33 provided where data output from the GPS is provided to
34 the processor.
35

36 23. Apparatus according to any of claims 19 to 22,

1 wherein the navigation apparatus is provided within a
2 housing which is mounted on an object, person, animal,
3 tool, vehicle, or any item for which knowledge of its
4 navigation is desired.

5

6 24. Apparatus according to any of claims 19 to 23,
7 wherein the inertial navigation sensor comprises three
8 orthogonally arranged sensors.

9

10 25. Apparatus according to claim 24, wherein the
11 inertial navigation sensors are solid-state devices.

12

13 26. Apparatus according to claim 25, wherein the
14 solid-state devices are solid-state accelerometers.

15

16 27. Apparatus according to either of claims 26,
17 wherein the solid-state devices comprise a silicon
18 etching formed in silicon wafer.

19

20 28. Apparatus according to any of claims 19 to 27,
21 wherein the artificial neural network is in the form of
22 a Kohonen Feature map.

23

24 29. Apparatus according to any of claims 19 to 27,
25 wherein the artificial neural network is in the form of
26 a Self-Organising Map (SOM).

27

28 30. Apparatus according to any of claims 19 to 29,
29 wherein patterns used to train the artificial neural
30 network represent patterns that will be observed in the
31 real data used during the "execution" phase of
32 operation.

33

34 31. Apparatus according to any of claims 19 to 30,
35 wherein many training cycles are conducted during the
36 training phase.

1 32. Apparatus according to any of claims 19 to 31,
2 wherein the artificial neural network is trained in an
3 unsupervised manner.
4

5 33. Apparatus according to any of claims 19 to 31,
6 wherein the artificial neuron network is trained in a
7 supervised manner.
8

9 34. Apparatus according to claim 33, wherein a
10 Backpropagation algorithm is utilised, wherein the
11 artificial neuron network adjusts its internal weights.
12

13 35. Apparatus according to claim 33, wherein data
14 representing the known locations is input to the
15 artificial neural network, prior to the next set of
16 data for the next location being input from the
17 inertial navigation sensor, such that the artificial
18 neural network learns the difference between the output
19 of the inertial navigation sensor versus the data
20 representing the known location.
21

22 36. Apparatus according to claim 32, wherein data
23 representing the known location is input to the
24 artificial neural network during the labelling phase of
25 the unsupervised training.
26

27 37. Apparatus according to any of claims 19 to 36,
28 wherein the inertial navigation sensor is moved between
29 many known locations of a track.
30

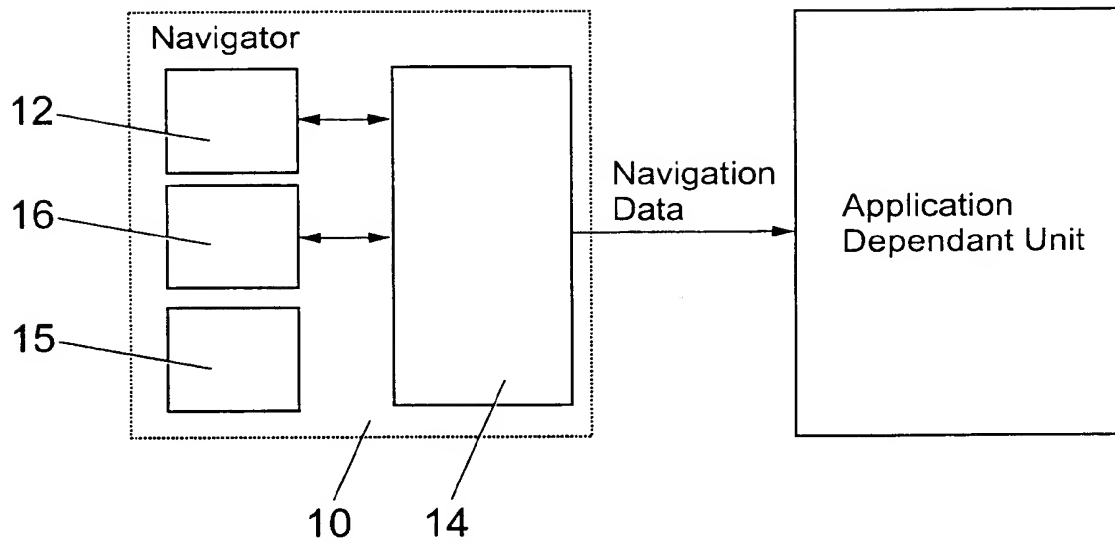
31 38. A method of providing navigation information, the
32 method comprising providing an inertial navigation
33 system having a non-linear output, and processing the
34 non-linear output with a processor, characterised by
35 the processor comprising an artificial neural network,
36 and moving the inertial navigation sensor between at

1 least two known locations during the training of the
2 artificial neural network.

3

4

1 / 2

*Fig. 1*

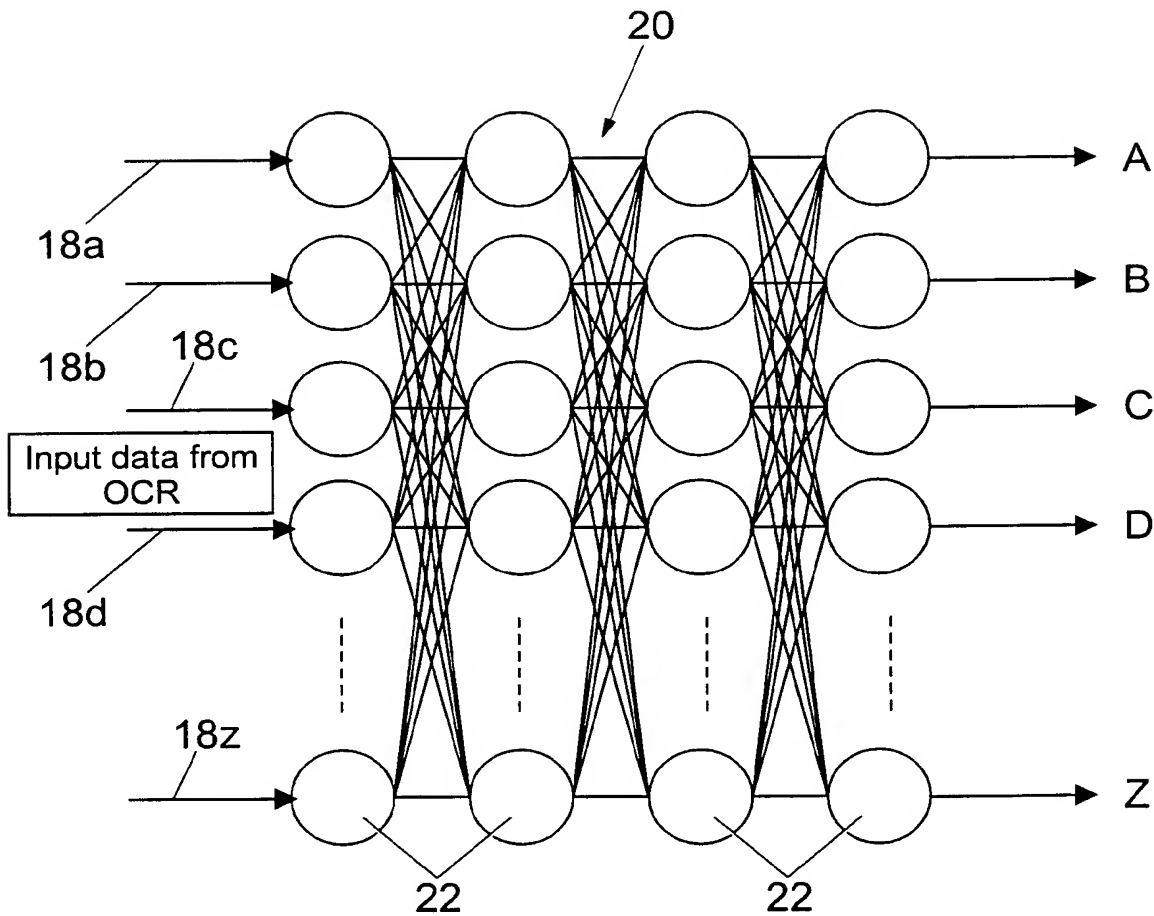


Fig. 2

INTERNATIONAL SEARCH REPORT

International Application No

PCT/GB 00/01966

A. CLASSIFICATION OF SUBJECT MATTER

IPC 7 G01S5/14 G01C21/16

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

IPC 7 G01S G01C

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practical, search terms used)

WPI Data, EPO-Internal, PAJ, INSPEC

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Category	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	US 5 654 890 A (LOSS KEITH R ET AL) 5 August 1997 (1997-08-05) figure 1 column 3, line 56 - line 61 column 9, line 41 - line 53 column 10, line 60 - line 67 ---	1-3, 5, 6, 18
A		19-38
X	EP 0 763 712 A (UNION SWITCH & SIGNAL INC) 19 March 1997 (1997-03-19) abstract	1-6, 19-23, 38
A	column 2, line 25 - line 38 column 4, line 46 - line 53 column 5, line 39 - line 48 column 6, line 10 - line 18 ---	24-37
	-/--	



Further documents are listed in the continuation of box C.



Patent family members are listed in annex.

Special categories of cited documents:

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"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art.

"&" document member of the same patent family

Date of the actual completion of the international search

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INTERNATIONAL SEARCH REPORT

In ternational Application No

PCT/GB 00/01966

C.(Continuation) DOCUMENTS CONSIDERED TO BE RELEVANT		
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